Employing ARIMA Forecasting Technique for Dengue Fever Outbreak Prediction in Toba Tek Singh and Jhang District: A Weather-Based Approach

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DECLARATION

I hereby declare that the work presented in the following thesis is my own effort, except where otherwise acknowledged, and that the thesis is my own composition. No part of this thesis has been previously presented for any other degree.

Tahseen Zafar

CERTIFICATE

It is certified that the dissertation "**Employing ARIMA Forecasting Technique for Dengue Fever Outbreak Prediction in Toba Tek Singh and Jhang District: A Weather-Based Approach**" by Tahseen Zafar, is accepted in its present form by the Department of Zoology, Faculty of Biological Sciences, Quaid-i-Azam University, Islamabad as satisfying the thesis requirement for the degree of Master of Philosophy in Parasitology.

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IN THE NAME OF ALLAH

THE MOST BENEFICENT

THE MOST MERCIFUL

Dedication

With profound love & deep respect, this dissertation is dedicated to my Parents, Mamu, and Aunty.

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LIST OF ABBREVIATIONS

Abrevations	Stands For
DEN	Dengue
F	Fahrenheit
WHO	Worls Health Organization
DF	Dangue Fever
DHF	Dengue Hemorrhagic Fever
DSS	Dengue Shock Syndrome
ARIMA	Autoregressive Integrated Moving Avergae
SARIMA	Seasonal Autoregressive Integrated Moving Avergae

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All the acclamations and appreciations are for ***Almighty ALLAH***, the compassionate and generous who knows best the mysteries and secrets of the universe, and his ***Holy Prophet Muhammad (Peace Be Upon Him)*** who has guided His Ummah to seek knowledge from cradle to grave and enabled me to win the honor of the life and whose teachings have served as a signal of light for the humanity in the hours of despair and darkness. I offer my humble and sincerest words of thanks to ***ALLAH Almighty*** that despite all the problems which I encountered during my M. Phil he enabled me to complete this dissertation.

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Tahseen Zafar

ABSTRACT

In many areas of Pakistan, Dengue is one of the most prevalent and fatal infections. In Pakistan, the frequency and geographic spread of Dengue Fever has grown during the previous ten years. Based on this context, an effort was made to transform the monthly data on Dengue Fever that was available from the two districts of Punjab during the previous four years into a seasonal ARIMA model to predict disease burden. To lower the prevalence of this condition, an accurate forecast-based model is necessary. DHF and other infectious diseases are studied and predicted using time-series methods in epidemiology, such as Autoregressive Integrated Moving Average (ARIMA) models. The current study used a time-series technique to try and predict the monthly verified DHF cases. The information was gathered from the Toba Tek Singh and Jhang District Head Quarter Hospitals and covered the period from March 2019 to December 2022. Several ARIMA models were implemented using Python and a sample data set, and the best seasonal ARIMA model was found. The chosen model was then applied to predict the monthly incidence of Dengue Fever starting in the following years, 2023 and 2024. The results showed that in comparison to any other model, the ARIMA (2,1,2) and ARIMA (2,0,2) models were able to predict the DHF epidemics in both Districts respectively. Using the ARIMA models, we further predicted DHF cases over 19-month intervals beginning in March 2023 and ending in December 2024. The findings revealed large seasonal DHF epidemics, especially from March to September. A substantial seasonal association between DHF and the ambient temperature was rev ealed by the highest instances, which were seen in August and September.

In Toba Tek Singh and Jhang City, this study is the first attempt to analyze the time-series model for DHF patients and forecast upcoming outbreaks.

The research could aid in the development of effective public health policies for disea se detection and management, particularly in the early stages of outbreaks.

Keywords: ARIMA model; forecasting; Dengue Fever; time-series analysis

INTRODUCTION

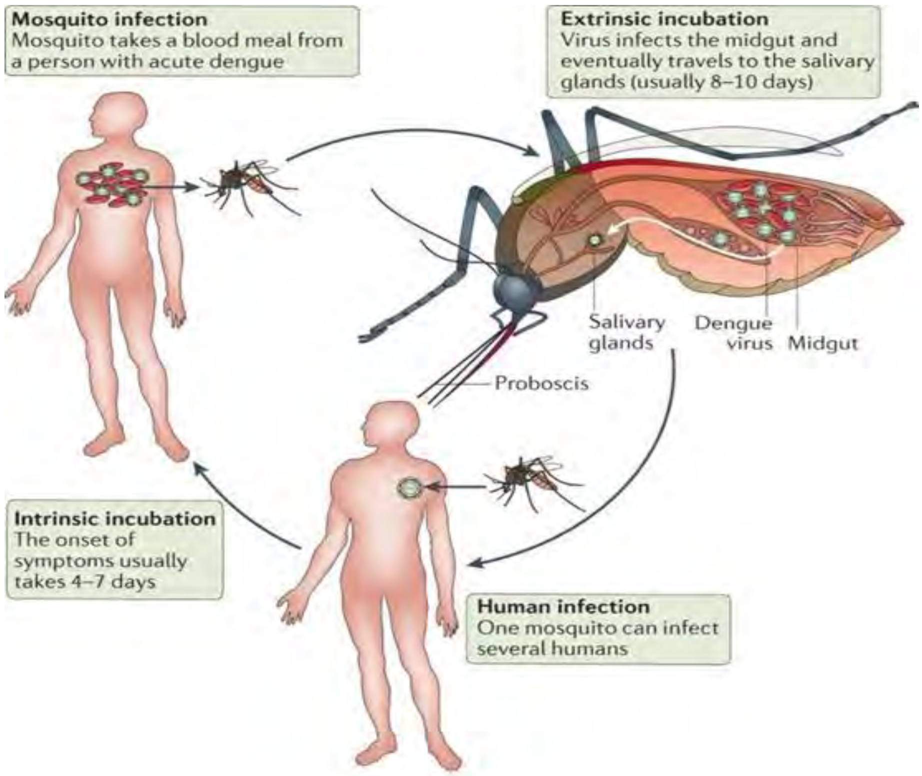
One of the most harmful and quickly virulent tropical illnesses is dengue. In some socio-ecological circumstances, its burden is comparable to that of malaria (WHO, 2014). It is a vector-borne viral disease that is a hazard to public health and has affected many tropical, subtropical, and temperate regions of the world, causing a significant socioeconomic burden (Ahmad *et al.,* 2017). The World Health Organization (WHO) estimated that 390 million Dengue Fever (DF) infections occur each year across 128 countries, putting 3.9 billion people at risk (Naqvi *et al.,* 2021). Almost 50 to 500 million people are thought to get Dengue infection every year on a global scale (Sutriyawan *et al.,* 2022). Two and a half billion individuals are at risk of infection, and between 10,000 and 20,000 people die each year (Abualamah *et al.,* 2021).

1.1 Causative Agent

Humans acquire Dengue disease from the four single-stranded positive polarity ribonucleic acid (RNA) viruses (DEN-1, DEN-2, DEN-3, and DEN-4) of the *Flavivirus* genus (WHO, 2014). However, DENV2 and DENV3 infections are more frequently associated with it, and both of these genotypes are the most frequently diagnosed ones in the Indo-Pak subcontinent. Although all four virus serotypes can cause severe and fatal hemorrhagic disease, they are more frequently linked to it (Khan *et al.,* 2013). The main vector that transfers the Dengue virus (DENV) from person to person is *Aedes aegypti. Aedes albopictus* can also spread it (WHO, 2014). In dense tropical urban regions, DENVs are sustained via an epidemic cycle involving humans and mosquitoes. In the past, within the rainforests of Asia and Africa, sylvatic cycles involving non-human primates and canopy-dwelling *Aedes spp*. mosquitoes gave rise to the highly domesticated principal vector mosquito, *A. aegypti*, and these viruses have since become fully adapted to humans (Guzman *et al.,* 2016).

1.2 Life cycle

The infection is acquired by the female mosquito when it ingests blood during the acute febrile and viraemic stage of the illness. 5–12 (usually 8–10) days after the virus initially infects midgut cells during the extrinsic phase of incubation, the salivary glands become infected. The viral strain, the mosquito's ability, and the temperature of the surroundings all have an impact on this process. Once the salivary glands are infected, the mosquito becomes contagious and can transmit the virus to another person while feeding on blood. The sickness can spread to everyone who is bitten by the mosquito or comes in contact with it as it searches for blood to consume. In humans, the intrinsic incubation period (the time between an infection and the onset of illness) lasts 3 to 14 days on average of 4 to 7 days (Guzman *et al.,* 2016).



(Guzman *et al.,* 2016)

Figure 1.1: The urban life cycle of Dengue virus in mosquitoes and humans.

1.3 Pathogenicity

Infection caused by Dengue virus can results in Dengue Fever (DF), Dengue hemorrhagic fever (DHF), or Dengue shock syndrome (DSS). Classical Dengue Fever is a mild, febrile illness that often follows an initial Dengue virus infection that is resolved in about seven days by a sophisticated immune response. Due to antibody-dependent improvement, severe dengue, such as DHF or DSS, which can be fatal, can be brought on by recurrent infections or infections with a different serotype. High-grade fever-enhanced vascular permeability, plasma leakage, hemorrhagic symptoms, and thrombocytopenia are the characteristics of these outcomes. Due to the unavailability of particular antiviral medications or vaccines, Dengue Fever results in an increasingly dangerous situation with its two serious clinical symptoms, Dengue DHF and DSS (Bulletin, 2006). Despite the fact that some Dengue Fever cases may show symptoms, Dengue Fever is more usually asymptomatic. DHF will incorporate warning signs for dengue, notably plasma leakage and severe Dengue Fever (Guha-Sapir and Schimmer, 2005).

1.4 Distribution of Dengue Worldwide

According to current data, 60% of the world's population will be susceptible to Dengue disease by 2080 (Messina *et al.*, 2019). According to this estimate, Dengue killed 10,000 lives worldwide, in more than 125 countries (Aziz *et al.,* 2014). In the last 50 years, the prevalence of Dengue has increased 30 times worldwide, and the lack of a reliable vaccine is making the threat even worse (Naqvi *et al.,* 2021). The actual origin of the virus is still up for debate, although numerous studies suggest it originated in Africa or Asia. One of the main problems with global health is Dengue infection and its current prevalence everywhere. The disease is now prevalent in more than 100 countries, compared to the time before 1970 when just nine nations had experienced major Dengue outbreaks (Irekeola *et al.,* 2022).

Although Dengue is still regarded as an imported illness in China, the incidence has substantially grown in recent years due to extended outbreak zones (Sang *et al.,* 2023). Chinese drawings from the 10th century describe Dengue disease, but Benjamin Rush published the first in-depth account of Dengue shock syndrome in 1780 (Naqvi *et al.,* 2019). Then, the Dengue slowly spread from the Southeast coastal region to central China and the Western region. Many nations have witnessed strong Dengue activity in 2019, making it one of the years with the most Dengue activity. Since 1980, the Americas Region recorded the most instances. Massive epidemics took place in

Tanzania and Nepal. The first statewide Dengue epidemic also hit Bhutan this year. (Sang *et al.,* 2023).

Although Dengue Fever has long been a health concern in many regions of Asia and Africa, its effects have recently gotten worse for a variety of reasons. The risk of Dengue transmission has increased as a result of the development of mosquito habitats brought on by urbanization, population growth, and climate change (Akram *et al.,* 2020). It has been hypothesized that human importation of Dengue from endemic areas, the recent geographic spread of *Aedes aegypti* mosquito vectors, and altered environmental conditions all contributed to the emergence of Dengue in northern regions. Pakistan is an example of several countries struggling to stop the spread of the illness into formerly dengue-free areas and are on the verge of experiencing endemic Dengue transmission (Wesolowski *et al.,* 2015).

1.5 Epidemiology of Dengue in Pakistan

Pakistan is a subtropical country that serves as the main reservoir for several vector-borne diseases, such as malaria, leishmaniasis, West Nile virus disease, Crimean-Congo fever, dengue, and Dengue hemorrhagic fever. A recently identified and swiftly spreading infectious disease in this region is Dengue Fever. The first evidence of Dengue infection in Pakistan was detected in Punjab in 1982, where 12 out of 174 individuals tested positive for the virus; all of these samples were taken between 1968 and 1978 (Khan *et al.,* 2013). Before the year 2011, when a significant Dengue epidemic with over 20,000 cases took place in the northeastern city of Lahore (Rasheed *et al.,* 2013), the distribution of Dengue viruses in Pakistan was mostly restricted to the southern city of Karachi. This epidemic resulted in significant morbidity and mortality. Khyber-Pakhtunkhwa (KP) and Punjab provinces in northeastern Pakistan saw a second significant pandemic in 2013, designating the areas as an expanding focal point for yearly Dengue outbreaks (Wesolowski *et al.,* 2015).

The floods linked to climate change were caused directly by heavy monsoon rains and glaciers melting after an intense heat wave. The flooding was deemed to be the worst in Pakistan's history and the worst in the globe since the floods in South Asia in 2020. The disastrous floods that happened in June 2020 are to blame for the spike in DF (Qureshi *et al.,* 2023). 48906 instances, including 183 deaths, were reported between January 1 and November 25, 2021, in all provinces: Punjab, KP, Sindh, and Balochistan, which were ICTs under federal supervision, and AJK autonomous areas. With 10,223 cases, or 21% of all cases, KP, a province on the border of Afghanistan, had the second-highest number of Dengue cases. Ten deaths also occurred from the disease (WHO, 2023).

According to the Integrated Disease Surveillance & Response System (IDSRS), KP province, on November 2, 2022, 19,327 cases were detected and 15 deaths as a result of them were reported (WHO, 2023). The inadequate healthcare system in Pakistan may be overwhelmed by the increasing number of DF patients. Natural disasters, deplorable socioeconomic situations, and climatic conditions are some more critical variables that lead to the increase of infection in Pakistan. Between June 14 and October 20, 2022, floods in Pakistan claimed the lives of 1739 individuals and resulted in $14.9 billion damage in to property and $15.2 billion in lost economic output (Qureshi *et al.,* 2023). Most Southeast Asian countries have had Dengue for a long time, but it has just recently spread to Pakistan and other parts of the Middle East and South Asia (Rasheed *et al.,* 2013).

1.6 Prevention and Control

Preparatory measures must be developed and implemented in order to avoid DF and other arboviruses as well as to respond to them. Early warning systems, entomological, environmental, and epidemiological surveillance, clinical case management, laboratory support, environmental controls, risk communication, vector control, and community mobilization are all necessary to achieve this goal (Qureshi *et al.,* 2023). Dengue Fever prevention and control initiatives have mostly concentrated on vector management techniques such as eradicating mosquito breeding grounds, applying insecticides, and adopting community-based interventions. There is also ongoing research into Dengue vaccines, and some intriguing candidates have shown effectiveness in clinical studies (Leung *et al.,* 2023). Instilling healthy lifestyle behaviors (such as not littering, storing trash, and preventing any containers from serving as a larval roost) can be characterized as preventive measures. However, this method is unable to accurately detect changes in prevalence (Bhatnaghar *et al.,* 2012).

The epidemiologic metrics help identify associated epidemiological factors and the efficacy of control strategies by tracking the trends and fluctuations of Dengue Fever. Epidemiological modeling can forecast future trends and outbreaks by using specific information about the times and locations of historical DF/DHF occurrences. This makes the health systems more capable of organizing and allocating resources for the efficient containment of upcoming outbreaks (Wang *et al.,* 2017). If a major outbreak like this could be anticipated, public health officials would have more time to put community preventive and mosquito control into place, which would help to contain the epidemic. However, it is still challenging to predict Dengue epidemics accurately. (Chen *et al.,* 2022).

1.7 Forecast-based early warning systems

An early warning system with forecasting capabilities is needed to lower the prevalence of this disease. Other forecasting models are in use throughout the world, including in Indonesia. These models can't, however, account for all the DHF data's properties because they're not effective enough. Therefore, it is imperative to create more adaptable forecasting models that can deliver superior outcomes than the ones now in use. This will help decision-makers in government make wiser choices (Suleiman *et al.,* 2021).

Researchers have discovered that inter-annual and seasonal climate fluctuation has a significant impact on Dengue virus transmission. For instance, it has been discovered that the temperature factor is a crucial climate variable that affects the occurrence of Dengue Fever. Temperature was found to be the best environment for adult mosquito survival as well as that of larva, pupa, and egg (in the aquatic phase) in an environmental experiment (Salim *et al.,* 2021). Because of the regional variance in vector habitat, climatic patterns, and subsequent human control measures, vector-borne illnesses frequently exhibit spatial heterogeneity (WHO, 2022). The pattern of Dengue transmission is determined by the interaction of human, climatic, and mosquito dynamics, which creates a complex system that affects the likelihood of an outbreak. Over the years, these connections have been studied in the global development of prediction models. The goals and contexts of models differ greatly (Bedenum *et al.,* 2018).

A prediction model must be systematic, self-adaptive, and generalizable to find weather and population susceptibility trends across geographical regions. Although many of these models are excellent at different tasks. The best prediction model has not yet been chosen by the scientific community. The choice of predictors for the current models is also rather diverse. Some models only take into account climate variables, while others include taking into account vector properties and demographic characteristics. Various statistical methods are employed by the existing models, with varied degrees of accuracy and resilience (Leung *et al.,* 2023).

1.8 Statistical Modelling

Statistical modeling is a practical method for forecasting Dengue outbreaks. In earlier research undertaken in China, India, Thailand, the West Indies, Colombia, and Australia, the time series technique was heavily utilized in the field of epidemiologic studies on contagious diseases (Naher *et al.,* 2022). In particular, the study of infectious disease epidemiology has made substantial use of the statistical technique known as time-series forecasting (Siregar *et al.,* 2017). In several research, statistical models that were created to predict Dengue in diverse contexts have been applied (Cummings *et al.,* 2009). Since DHF data exhibit time-varying behavior, seasonal patterns, secular trends, and quick swings in time series, it is possible to estimate the occurrence of the disease using time-series techniques to enable an early response to the illness (Banditvilai and Anansatitzin, 2018). Popular time series models include the autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), and ARIMA models (ARIMA). All of these are useful, though, as long as there is currently just an effective linear serial correlation between the data sets (Riaz *et al.,* 2023).

The ARIMA technique, which has been widely used because of its significance and ability to handle both stationary and non-stationary time series data, is one of the most important statistical methods in the analysis of time series studies for forecasting. As its linearity assumption is linked to time series, this technique is effective for data with linear conditions. Models with an ARIMA structure have greater predictive potential than other approaches due to the transmissibility and seasonality of malaria; over the years, these models have been used to forecast many infectious diseases with comparable periodic patterns (Riaz *et al.,* 2023). The use of time series analysis-based Auto Regressive Integrated Moving Averages (ARIMA) modeling in the field of epidemiological research on infectious diseases such as influenza, malaria, and Dengue is on the rise (Wang *et al.,* 2017).

A common time-series forecasting method used in health science research is the autoregressive integrated moving average (ARIMA) (Najera *et al.,* 2022). The premise behind statistical forecasting techniques like ARIMA is that the time series can be made to appear roughly stationary. A stationary time series is one in which the mean and variance, for example, remain constant over time. A predictive forecasting model has been created using time series data and autoregressive integrated moving average (ARIMA) models for statistical modeling and analysis (Wang *et al.,* 2017).

The ARIMA model consists of three parts: "AR (Auto Regression)", "I (Integration)" and "MA (Moving Average)". The "AR" portion denotes a regression on prior values for the projected variable of interest. The "I" component indicates that the data values have been replaced with the difference between the new and old values. The regression error is effectively an average of error terms whose values occurred both concurrently and at different moments in the past, according to the "MA" component. Each of these features enhances the model's capacity to match the data. There are two types of ARIMA models. There are additional seasonal and non-seasonal ARIMA models available. The standard notation for non-seasonal ARIMA models is ARIMA (p, d, q), where p is the order (number of time lags) of the autoregressive model and the other three parameters are non-negative integers. It enables adding the impact of previous values to the model. This is equivalent to saying that if it has been warm recently, it will likely be warm tomorrow. This is equivalent to saying that if it has been warm for the last three days, it will probably be warm tomorrow (Nayak and Narayan, 2019).

‘d’ is the amount of differencing (the number of times the variables have had prior values eliminated) to make the model stationary, or to prevent a rising or falling trend. If the difference in temperature over the previous three days was minimal, it would be akin to declaring that the temperature will remain the same tomorrow. How to calculate the average temperature for a given day based on the prior and subsequent 1, 3, 5, and 7 days depends on the moving-average model's order or size, ‘q’. The standard form of a seasonal ARIMA model is stated as ARIMA (p, d, q) (P, D, Q)m, where m is the number of seasons and the capital letters P, D, and Q stand for the model's moving average, autoregressive, and differencing elements, respectively. A seasonal ARIMA model can be used if more than a year's worth of data is available, while a non-seasonal ARIMA model can be used if only a few months' worth of data is available (Hyndman and Athanasopoulos, 2018).

So establishing an accurate Dengue forecasting system in the Toba Tek Singh and Jhang districts of the province of Punjab could give local health officials and policymakers useful information. It may aid in setting priorities for funding, concentrating vector control efforts, and directing public health initiatives toward Dengue transmission hotspots. Additionally, a strong forecasting system would enable proactive actions like improved surveillance, timely warning of risks to communities and healthcare professionals, and resource mobilization for epidemic response

1.9 Aim and Objectives

The present study is aimed to predict Dengue outbreaks by utilizing previous Dengue data and a statistical ARIMA Model.

 To forecast the Dengue outbreaks using a time-series model from 2019 to 2022 data for twenty-two months prediction covering March 2023 to December 2024.

 To analyze the effects of weather on Dengue outbreaks in Toba Tek Singh and Jhang Districts.

MATERIALS AND METHODS

2.1 Study Area

The present study was conducted in the two districts of Central Punjab i.e. Toba Tek Singh and Jhang. Toba Tek Singh is situated between latitudes 30°33 and 31°20' North and 72°08 and 72°48' East. Additionally, it takes up 3252 square kilometers of space. The side district Jhang is located between 71°37 and 73°13 East longitudes and 30°37 to 31°59 North latitudes. The climatic conditions in the two districts *Aedes spp.* mosquito breeding and Dengue virus transmission. High humidity during the monsoon season and hot summer temperatures create ideal conditions for mosquito breeding and virus reproduction.

Fig 2.1 Map showing the study geographical area in Central Punjab i.e. District Toba Tek Singh and District Jhang.

2.2 Data Collection

The secondary source of data for this study consisted of Dengue cases reported in the District Headquarters Hospitals of Toba Tek Singh and Jhang City. The data collection process spanned approximately two months, encompassing Dengue cases reported within the last four years. Hospital records served as the foundation of our dataset, enabling us to extract a comprehensive set of variables to be analyzed.

2.3 Data Analysis

Our analysis plan was aimed to extract meaningful insights from the collected data. Descriptive statistics were employed to summarize and present the data effectively. Categorical variables, such as age groups and gender, were presented using frequency distributions and percentages. Measures of central tendency (mean) and measures of variability were used to summarise continuous variables, including age and laboratory measurements (standard deviation). Data was arranged using statistical tools i.e. MS Excel.

2.4 Exploratory Data Analysis (EDA)

Descriptive statistics were computed to gain insights into the central tendency and dispersion of the Dengue Fever cases and weather variables. To arrange raw data measures such as mean, median, and standard deviation were calculated to understand the data distribution. Visualizations, including line plots, bar charts, and heat maps, were created to visualize trends, seasonality, and potential relationships between Dengue cases and weather parameters.

2.5 ARIMA Model Formulation

The Autoregressive Integrated Moving Average (ARIMA) model, a well-known time series forecasting method, was used to forecast Dengue Fever outbreaks. Three major elements—Autoregressive (AR), Integration (I), and Moving Average (MA)—define the ARIMA model. These elements accurately depict the stationarity, temporal dependencies, and noise in the time series data. The application of prior observations to forecast future values is referred to as the AR component. The number of lag observations included in the model is indicated by the order of the autoregressive component (p). The 'I' component stands for differencing, a technique used to make the time series data stationary. The number of differencing applications necessary to reach stationarity is indicated by the order of differencing (d). The MA component takes into consideration the impact of earlier forecasting errors on upcoming values. The amount of lags in the model's forecast mistakes is indicated by the order of the moving average component (q) (Othman et al., 2022). The ARIMA (p, d, q) model was chosen after determining the proper values of p, d, and q for our dataset by examining autocorrelation and partial autocorrelation plots. The seasonal ARIMA is known as SARIMA. Seasonality in time-series analysis refers to a predictable pattern of fluctuations that repeats itself throughout s periods, where s is the interval between repetitions. The monthly data, for instance, exhibit seasonality. There are some months where high values are more common than low values (Othman *et al.,* 2022).

This model can be denoted by:

SARIMA (p, d, q) (P, D, Q)s -------------------------------------- (1)

2.6 Model Fitting and Validation

The ARIMA (p, d, q) model was fitted to the training dataset using Python version (3.9). The training dataset was used to estimate the model parameters. The seasonal component identified during time series decomposition was incorporated into the model to capture seasonality in the data.

The model's performance was validated using the testing dataset using statistical tools i.e. Python (version 3.9) to quantify the difference between predicted and actual Dengue cases.

2.7 Outbreak Prediction and Interpretation

The validated ARIMA model was employed to forecast Dengue Fever outbreaks based on fresh weather data. The model generated point forecasts as well as confidence intervals, which provided insights into the uncertainty of the predictions. The implications of the model's forecasts were interpreted within the context of public health planning and preparedness.

RESULTS

3.1 Seasonal Trends and Weather Correlation

Seasonal trends and weather correlation in Dengue infection are essential for predicting outbreaks and shaping effective public health responses. Dengue cases often follow distinct seasonal patterns, tied to mosquito activity, while weather factors like temperature, humidity, and rainfall influence mosquito populations and virus transmission. Analyzing historical data reveals these patterns and correlations, enabling early warnings and targeted interventions.

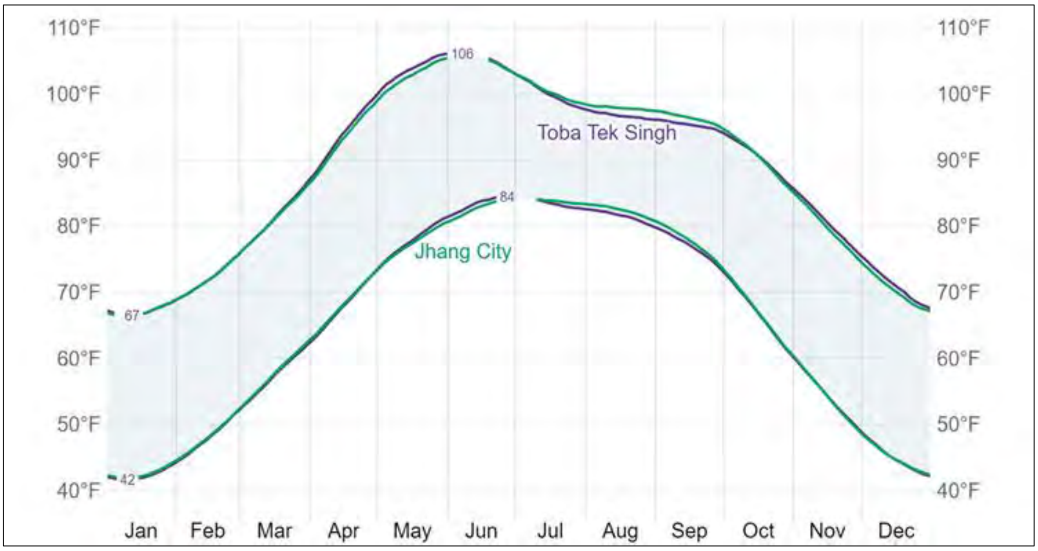


Figure 3.1 Seasonal variation of temperature in District Toba Tek Singh and Jhang during the year 2019.

The fluctuation of temperature is shown in Figure 3.1 side by side in both districts of Punjab throughout the year 2019. It is seen in the above graph that temperature gradually starts increasing from March till September during the whole year. The peak temperature is recorded at the end of May giving rise to the production of mosquitoes and hence increasing the number of Dengue cases. The highest temperature recorded during this year ranges from 84°F to 106°F, which is quite favorable for the production of mosquito-causing dengue. By comparing this temperature with the average monthly number of Dengue cases in the year 2019, weather correlation can be observed easily.

Figure 3.2 Seasonal variation of temperature in District Toba Tek Singh and Jhang during the year 2020.

The graph in Figure 3.2 depicts the seasonal variation of temperature in Toba Tek Singh and Jhang City for the year 2020 and holds significance in the context of Dengue Fever cases. The understanding of temperature trends can indirectly impact disease transmission. The x-axis represents the months, and the y-axis represents the temperature. The graph demonstrates the changing temperature patterns throughout the year 2020, with temperatures generally increasing during summer months up to 106°F and decreasing during winter months up to 75°F. Similar to the graph showing weather correlation in the year 2019, this temperature fluctuation can also be compared with month-wise number of Dengue Fever cases. This visual representation aids in identifying potential patterns that could impact factors like mosquito activity and disease transmission, offering valuable information for understanding the dynamics of Dengue Fever outbreak risks and supporting targeted public health interventions and preparedness efforts in both Toba Tek Singh and Jhang in the year 2020.

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Figure 3.3 Seasonal variation of temperature in District Toba Tek Singh and Jhang during the year 2021.

Figure 3.3 illustrates the interplay between weather fluctuations and temperature in both the Toba Tek Singh and Jhang districts throughout the year 2021. The temperature trends for both districts are depicted by distinct lines. The graph shows how the temperature changes align with various weather fluctuations experienced in each district. Similar to the figure 3.2.

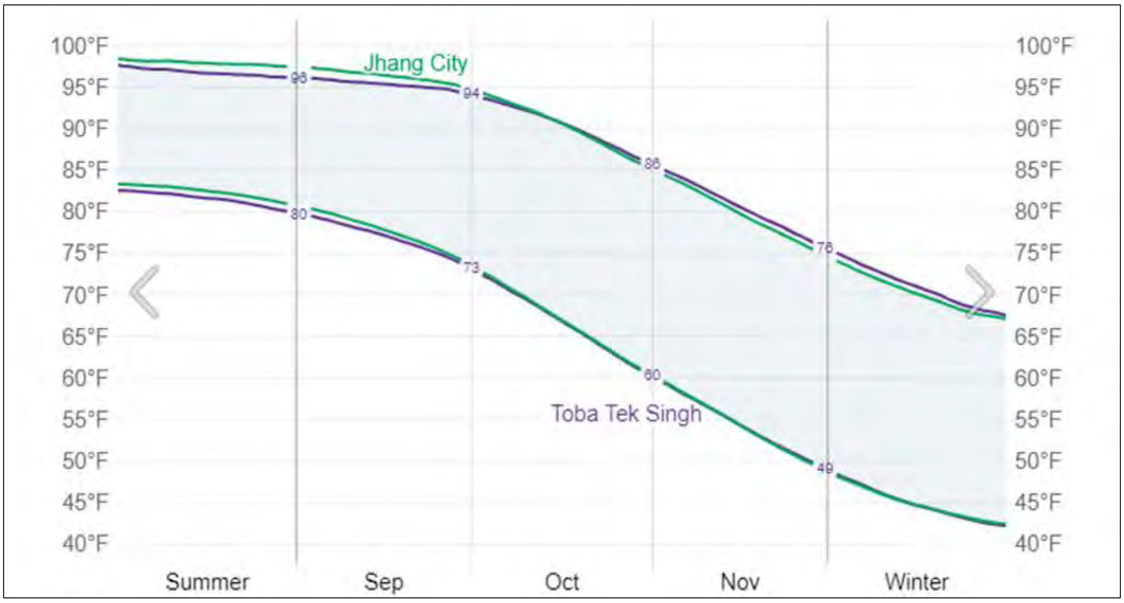

Figure 3.4 Seasonal variation of temperature in District Toba Tek Singh and Jhang during the year 2022.

Figure 3.4 illustrates that the temperature in the summer seasons of both districts in the year 2022 lies between 80°F and 90°F. In the winter season, the temperature of both districts falls up to 42°F. This temperature difference shows a significant increase and decrease in Dengue cases in the year 2022. The lines showing up and down fluctuations in the temperature of both districts correlate with Dengue cases

3.2 Monthly Data Analysis

i) District Toba Tek Singh

Months	Year 2019	Year 2020	Year 2021	Year 2022
March	90	124	22	83
April	70	90	80	147
May	110	121	79	192
June	115	101	113	226
July	200	231	120	253
August	250	317	129	275
September	275	289	173	318
October	215	237	142	291
November	185	211	111	207
December	101	190	104	196

Table 3.1 Number of Dengue Fever cases in District Toba Tek Singh for each month from the year 2019 to 2022.

Table 3.1 shows a comprehensive overview of the number of reported Dengue Fever cases in District Toba Tek Singh for each month spanning from the year 2019 to 2022. Each row in the table corresponds to a specific month, while the columns represent the years 2019, 2020, 2021, and 2022, with the respective number of Dengue cases reported for each month and year.

March: In March, the data reveals that there were 90 reported cases of Dengue Fever in the year 2019. This count increased to 124 cases in 2020, decreased substantially to only 22 cases in 2021, and then increased again to 83 cases in 2022.

This demonstrates a notable fluctuation in cases, especially the substantial drop in 2021 compared to the surrounding years.

April: April exhibited 70 reported cases in 2019, which slightly increased to 90 cases in 2020, dropped to 80 cases in 2021, and significantly escalated to 147 cases in 2022. This data highlights the fluctuations in cases, with a significant spike in 2022.

May: May experienced 110 cases in 2019, which increased slightly to 121 cases in 2020, dropped to 79 cases in 2021, and then surged dramatically to 192 cases in 2022. The data underscores the considerable variations in reported cases, especially the substantial increase in 2022.

June: In June, the reported cases were 115 in 2019, decreasing to 101 cases in 2020, increasing to 113 cases in 2021, and rising significantly to 226 cases in 2022. This data showcases fluctuations in cases, with a notable increase in 2022.

July: July saw 200 reported cases in 2019, which rose to 231 cases in 2020, decreased to 120 cases in 2021, and then increased to 253 cases in 2022. The data reflects fluctuations in cases, with a significant increase in 2022.

August: August experienced 250 cases in 2019, increasing to 317 cases in 2020, further dropping to 129 cases in 2021, and then increasing again to 275 cases in 2022. This data demonstrates fluctuations in cases, with a notable decrease in 2021 followed by an increase in 2022.

September: In September, the reported cases were 275 in 2019, which slightly increased to 289 cases in 2020, decreased to 173 cases in 2021, and then surged to 318 cases in 2022. This data highlights fluctuations in cases, with a significant increase in 2022.

October: October saw 215 reported cases in 2019, which slightly increased to 237 cases in 2020, decreased to 142 cases in 2021, and then rose to 291 cases in 2022. The data underscores fluctuations in cases, with a substantial increase in 2022.

November: November experienced 185 cases in 2019, which increased to 211 cases in 2020, dropped to 111 cases in 2021, and then increased to 207 cases in 2022. The data reflects variations in cases, especially the drop in 2021.

December: In December, the reported cases were 101 in 2019, increasing to 190 cases in 2020, decreasing to 104 cases in 2021, and then jumping to 196 cases in 2022. This data showcases fluctuations in cases, with varying patterns over the years.

This comprehensive Table 3.1 provides an in-depth understanding of the seasonal variations in Dengue Fever cases across different months and years. It underscores the fluctuations, increases, and decreases in reported cases, which can offer valuable insights for public health planning, resource allocation, and surveillance efforts.

ii) District Jhang

Months	Year 2019	Year 2020	Year 2021	Year 2022
March	23	9	467	458
April	191	258	565	452
May	287	424	677	544
June	394	504	760	515
July	450	473	824	587
August	482	434	836	627
September	531	541	1081	663
October	598	602	1046	683
November	472	512	785	561
December	101	415	527	466

Table 3.2 Number of Dengue Fever cases in District Jhang for each month from the year 2019 to 2022.

Table 3.2 presents a comprehensive overview of the number of reported Dengue Fever cases in District Jhang for each month of the years 2019, 2020, 2021, and 2022. Each row of the table corresponds to a specific month, while the columns represent the respective years.

March: In March, the data showcases significant variations in reported cases over the years. The cases were 23 in 2019, dropped to 9 cases in 2020, and then underwent a dramatic surge to 467 cases in 2021. There was a slight decline to 458 cases in 2022. This marked increase in 2021 followed by a stabilization in 2022 suggests potential changes in disease transmission dynamics during this period.

April: April demonstrates fluctuations in cases. Starting with 191 cases in 2019, the count increased to 258 cases in 2020, peaked at 565 cases in 2021, and then decreased to 452 cases in 2022. The substantial spike in 2021 and subsequent decrease in 2022 highlight the dynamic nature of cases during this month.

May: May shows a consistent upward trend in cases. Beginning with 287 cases in 2019, the count increased to 424 cases in 2020, surged to 677 cases in 2021, and then slightly declined to 544 cases in 2022. This clear upward trajectory across the years points to the potential seasonality of the disease during this period.

June: June reveals fluctuations in cases. Starting with 394 cases in 2019, the count increased to 504 cases in 2020, experienced a peak at 760 cases in 2021, and then decreased to 515 cases in 2022. The notable peak in 2021 followed by a decrease in 2022 signifies changing patterns in disease transmission during this period.

July: July demonstrates fluctuations with varying peaks. The cases were 450 in 2019, slightly increased to 473 cases in 2020, spiked to 824 cases in 2021, and then decreased to 587 cases in 2022. The significant spike in 2021 followed by a decrease in 2022 highlights the dynamic nature of cases during this month.

August: August displays fluctuations with varying peaks. Starting with 482 cases in 2019, the count decreased to 434 cases in 2020, surged to 836 cases in 2021, and then decreased to 627 cases in 2022. The substantial peak in 2021 followed by a decrease in 2022 illustrates changing patterns in disease transmission during this period.

September: September exhibits substantial fluctuations. The cases were 531 in 2019, increased to 541 cases in 2020, dramatically surged to 1081 cases in 2021, and then decreased to 663 cases in 2022. This significant increase in 2021 followed by a decrease in 2022 highlights dynamic changes in disease transmission during this month.

October: October shows fluctuations with varying peaks. Beginning with 598 cases in 2019, the minimal increased to 602 cases in 2020, spiked to 1046 cases in 2021, and then slightly decreased to 683 cases in 2022. The notable peak in 2021 followed by a decrease in 2022 illustrates potential shifts in disease transmission dynamics during this period.

November: November demonstrates fluctuations with varying peaks. The cases were 472 in 2019, increased to 512 cases in 2020, spiked to 785 cases in 2021, and then decreased to 561 cases in 2022. The substantial peak in 2021 followed by a decrease in 2022 points to changing patterns in disease transmission during this month.

December: December showcases fluctuations with varying peaks. Starting with 101 cases in 2019, the count increased to 415 cases in 2020, peaked at 527 cases in 2021, and then slightly decreased to 466 cases in 2022. The notable increase in 2021 followed by a decrease in 2022 illustrates potential shifts in disease transmission dynamics during this specific period.

To summarize, this detailed description of Table 3.2 highlights the intricate variations, fluctuations, and trends in reported Dengue Fever cases across different months and years. The data provides critical insights into the seasonal patterns, potential risk periods, and changing disease transmission dynamics, all of which are essential for effective public health interventions and preparedness strategies.

3.3 Data Visualization

The obtained data from the last four years is visualized in the form of bar graphs to make a correlation between increasing Dengue cases with weather conditions. Both Districts show fluctuation in the Dengue cases based on slight differences in their weather conditions. As in the weather plots that are shown at the start of the results, there is a corresponding change in the increase and decrease of Dengue cases throughout the four years. Both plots depicted below give fluctuation in weather as well as the reported number of cases over these years and this data is plotted further to show predicted values in the coming years through ARIMA modeling.

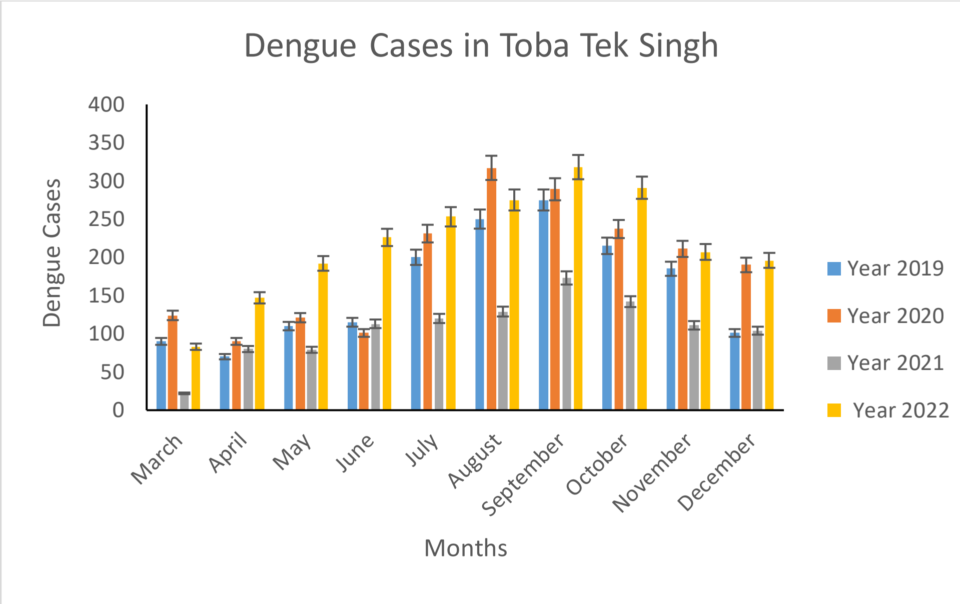

Figure 3.5 Shows the number of Dengue Fever cases in District Toba Tek Singh during different months of the years (2019-2022).

The data in Table 3.1 is visualized in the form of a column chart (Figure 3.5). The column chart effectively visualizes the dynamics of Dengue Fever cases in District Toba Tek Singh across various months and years, spanning from 2019 to 2022. Each vertical column on the chart represents a specific month, while the column heights depict the number of reported Dengue cases. The chart offers a clear and intuitive way to understand the temporal variations in cases.

Notably, the months of April, May, June, July, and September exhibit distinctive upward trends in Dengue cases across the four years. April, for instance, displays a gradual rise from 70 cases in 2019 to 147 cases in 2022. May experience fluctuations, but there's a remarkable surge in cases during 2022, reaching 192 cases. June, July, and September show consistent increases over the years, with June seeing a substantial jump to 226 cases in 2022.

Conversely, some months demonstrate varying patterns. March experienced a significant drop in cases in 2021 after relatively higher numbers in the preceding years. August showcases a dip in cases during 2021, followed by a rebound in 2022. Similarly, November witnessed a dip in 2021 after an increase in 2020. December showcases fluctuations, with a notable increase in 2020, followed by a decrease in 2021 and a subsequent moderate increase in 2022.

The column chart allows us to identify seasonal patterns and fluctuations in Dengue cases, offering insights that can aid in targeted public health interventions and preparedness efforts. The distinct patterns observed across the years highlight the dynamic nature of disease transmission and emphasize the importance of continuous monitoring and response strategies

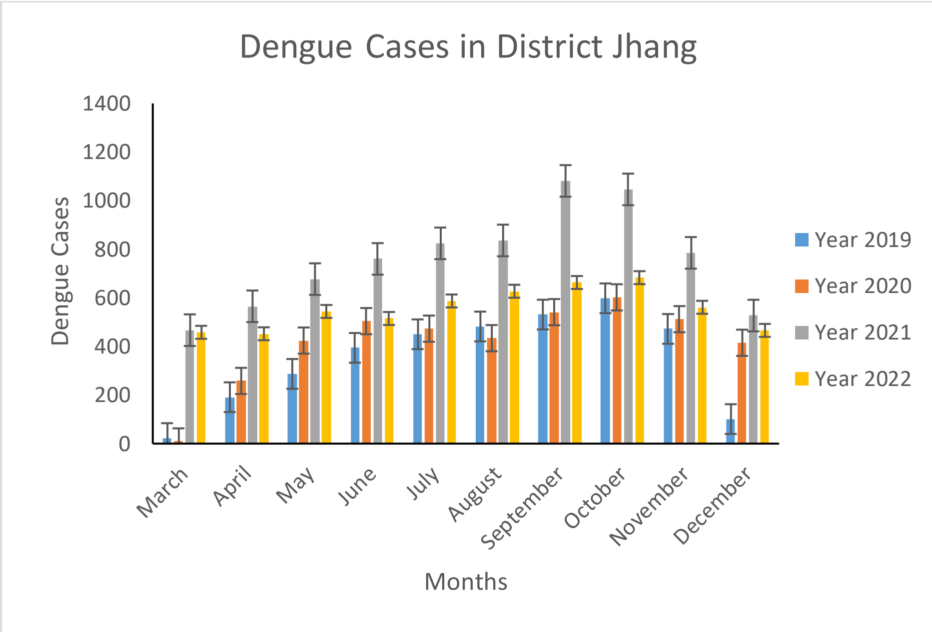

Fig 3.6 Shows the number of Dengue Fever cases in District Jhang during different months of the years (2019-2022).

The column chart prominently shows peaks in reported Dengue Fever cases in District Jhang across the years 2019 to 2022. Each distinct vertical column represents a specific month, with column height reflecting the number of cases reported. Notable peaks stand out, notably in March, April, and September, October of 2021. These peaks indicate significant surges in Dengue cases during these periods. The chart effectively visualizes the intensity of outbreaks, emphasizing critical points for heightened vigilance, rapid response, and resource allocation to manage the disease. Such pronounced peaks underscore the importance of targeted interventions and preparedness strategies to address and mitigate the impact of the Dengue outbreak.

3.4 ARIMA Forecast and Actual Dengue Cases Plot

Actual Dengue cases are shown in blue on the graph above, best predictions are shown in orange, and combined forecasting is shown in green. These lines' dots represent the months of the years 2019 through 2024. Figure 3.7 shows the actual, fitted, and predicted Dengue cases in District Toba Tek Singh to show how this model is fitted with the real data points. It is a simple approach to verify that our model's fitted line is straight before the accuracy measurement. It is clear from Figure 3.7 that this model is practically perfectly suited.

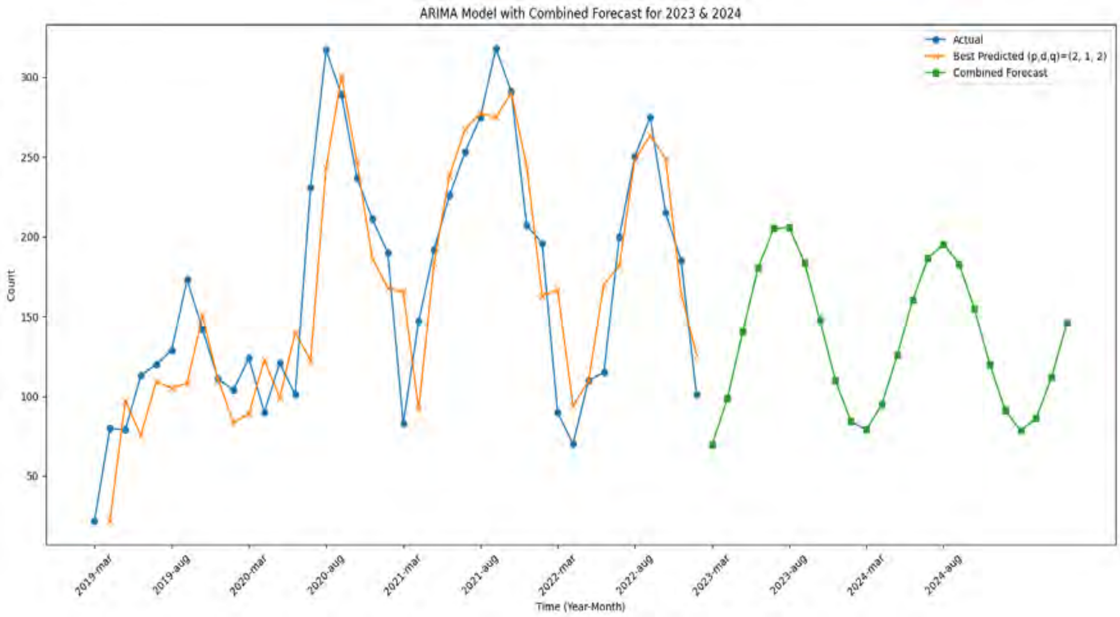

Fig 3.7 The actual monthly Dengue Fever cases from 2019-2022 and the monthly Dengue Fever cases predicted for 2023 and 2024 by using the ARIMA model in the District Toba Tek Singh.

Finally, we used the chosen ARIMA (2,1,2) model to forecast the final 2 years (March 2023 to December 2024). Additionally, the point forecast includes lower and upper alternative values with 95% and 80% confidence intervals. It indicates that with a 95% or 80% level of confidence, the point forecast may fluctuate within the upper and lower boundary. As a result, in the context of District Toba Tek Singh, the Dengue forecasting provided by this model is the superior representation. The results show that there will be a rise in Dengue cases in May and August over the study's forecasting period.

According to Figure 3.8, the monthly Dengue cases in the district of Jhang from 2019 to 2022 displayed a seasonal pattern, greatly grew during the study period, and then significantly decreased at the end of 2022. The number of Dengue cases in the District Jhang per month started to rise in March, reached a peak in August, and then started to fall. The seasonal changes in this plot of the reported Dengue cases led to its designation as non-stationary

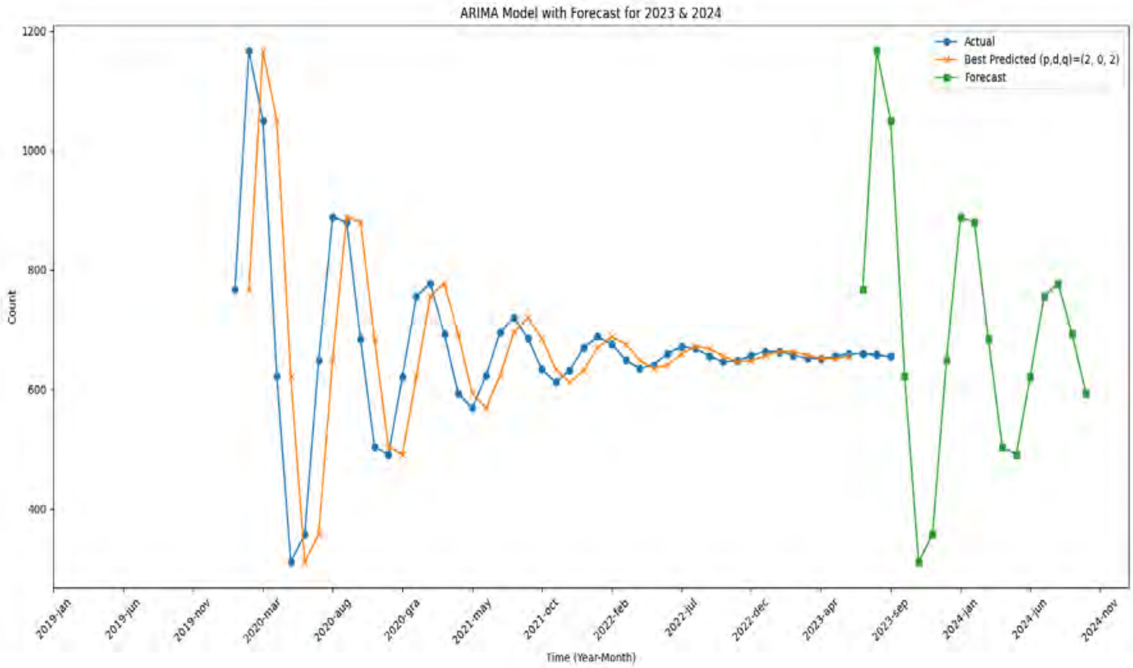

Fig 3.8 The actual monthly Dengue Fever cases from 2019-2022 and the monthly Dengue Fever cases predicted for 2023 and 2024 by using the ARIMA model in Jhang district.

The ARIMA (2,0,2) model was developed using information gathered between March 2019 and December 2022. The model's reliability was examined by projecting monthly DHF cases for 2023 and 2024 in this area. The outcome, as displayed in Figure 3.8 demonstrates that the actual value and the anticipated value were rather closely matched. The ups and downs of the observed series seemed to be reasonably well followed by the projected values. Similar to prior climatic changes, the cases displayed a seasonal pattern, peaking in September with an estimated 1000 cases or more. Dengue's momentum would start in May 2023, reach its peak in September, and then start to diminish towards December 2023. The year 2024 would display somewhat different peaks, predicting a high number of cases in March and a similar pattern of increased cases in September. Depicting the correlation of weather with an increasing number of cases. Temperature and weather conditions during these months are favorable for the breeding of mosquito larvae.

DISCUSSION

These circumstances are brought on by the summer monsoon, which dominates Pakistan's subtropical temperate climate and produces blazing and burning temperatures (particularly post-monsoon). Under these post-monsoon conditions, the *Aedes aegypti* mosquito, which spreads Dengue Fever, can mature and reproduce. These favorable conditions are complicated by a lack of infrastructure, unstable water availability that forced locals to store water for use at home, low educational attainment or high rates of illiteracy, poor sanitation, and a rise in population growth (Suleman *et al.,* 2016). Even though these conditions significantly increase the high mosquito density, the climate is the major factor that predominately influences DF transmission.

The evolution of Dengue has been influenced by a variety of factors, including insufficient disease and vector observations, a lack of public health infrastructures or organizations, an increase in population, unplanned and mismanaged urbanization, and changing climatic conditions (Vanzie, 2008). Dengue is usually found in hot, humid areas of the world, although its origin and spread are thought to be primarily influenced by fluctuating climatic conditions. Numerous studies have discovered a strong relationship between climatic factors and dengue, especially in terms of their seasonal cycles (Naqvi *et al.*, 2019). The minimum and maximum temperature are major weather predictors for the rise in Dengue Fever cases, according to a study on the relationship between weather factors and Dengue cases in Singapore using data from 2000–2007; however, rainfall and relative humidity have less of an impact (Pinto *et al.*, 2011).

In the present study, we applied statistical techniques like ARIMA to ascertain the variability of climatic conditions and their impact on Dengue incidence in districts Jhang and Toba Tek Singh. We estimated Dengue cases for the next two years using data from the past four years and the ARIMA Model. The average line for climatic factors has risen throughout the previous 43 years of investigation around the globe, according to previous studies. This upward trend line demonstrates how the climate in Pakistan is rapidly changing (Hii, Y *et al.,* 2012).

Modern technological improvements have made it simpler to predict regional and local weather with higher accuracy and lead times. This helpes to understand how climate affects both the spatial and temporal distribution of infectious diseases and assists in epidemic forecast modeling research, according to WHO (2004). We have estimated the data for the next two years using a weather-based Dengue forecasting model, which is based on the scientific evidence that temperature has a significant impact on Dengue vectors and viruses.

Climate factors have an impact on the structure of the mosquito population and their capacity to transmit disease. The ARIMA model used in this study revealed the influence of a relative temperature increase on Dengue transmission in Central Punjab, Pakistan. Our findings show that in the year 2020, temperatures generally continued to rise during the summer months up to 106°F and decline during the winter months up to 75°F. In the next two years, 2021 and 2022, both districts in Punjab had a temperature rise, however, there was little variation in the distribution of Dengue disease within and between the two districts. According to Liu-Helmersson *et al.* (2014), the study period's average temperature of 93°F was likewise near the ideal temperature for Dengue transmission. Similar findings were made in the earlier investigation held in China conducted by Sun *et al.,* (2017).

Rainfall often boosts mosquito breeding grounds; however, this study found that its effect on Dengue transmissibility was limited. In the city region of Jhang, there were many man-made water storage containers, such as jars, drums, and used tires, which are largely independent of rainfall. In the city, they developed into areas of mosquito breeding. Additionally, mosquito breeding grounds were made possible by standing water and unhygienic behaviors. On the other hand, a lot of rain can wash away mosquito breeding grounds and halt the development of mosquito eggs or larvae. According to the seasonal trend, the Dengue endemic peaked in both districts throughout the research period from August onwards, which is typically following the rainy season. These findings were consistent with a 2018 study that demonstrated that excessive rainfall flushes out *Aedes spp.* larvae from the nesting site and that following dry spells limit *Aedes spp.* breeding by preventing the creation of sufficient breeding sites (Benedum *et al.,* 2018).

The number of cases of Dengue Fever recorded in District Toba Tek Singh for each month from the years 2019 to 2022 is examined in this study. The findings showed that the monthly temperatures in both districts of Central Punjab fluctuated between 80°F and 106°F in March, April, August, and September, respectively. Summer seasons are thought to be the ideal environment for the growth of *Aedes spp.* and, as a result, the spread of Dengue Fever. Both districts have been found to exhibit seasonal trends in the hot weather, making this the ideal time of year for Dengue to arise. Additionally, between the years of 2019 and 2022, this study focuses on the complex variations, fluctuations, and trends in recorded Dengue Fever cases of District Jhang. The results show high maxima in several months of 2021, most notably in March, April, and September. These peaks show notable increases in Dengue cases during these times. The significance of focused interventions and preparatory tactics to address and lessen the effects of the Dengue outbreak is highlighted by such pronounced peaks. These results are consistent with the earlier results, however, there are a few minor deviations because of geographical and climatic changes (Duarte *et al.,* 2019).

Many researchers forecast the number of Dengue Fever cases using predictive ARIMA models. The majority of researchers employed seasonal ARIMA forecasting models and data from multiple years for their analyses. The present investigation followed the same process. The current study used a four-year monthly incidence dataset of Dengue Fever cases in the two districts of Punjab from the years 2019 to 2022. The best model for predicting the occurrence of Dengue Fever cases in the upcoming days, weeks, months, or years was found to be ARIMA (2,0,2) in the case of District Jhang and ARIMA (2,1,2) in the case of District Toba Tek Singh. Healthcare administrators can use this model to forecast events for the upcoming period. If the appropriate data is made available, shorter-term forecasts are possible. Similar findings were made in the Indian study carried out by Rajisthan researchers (Bhatnagar *et al.,* 2012). The variations in the p, d, q values, and P, D, Q values of the seasonal ARIMA model between studies could be attributed to local environmental factors and the accessibility of healthcare services.

Additionally, from May 2023 to November 2024, a 19-month out-of-sample forecasting of outbreaks of Dengue was done for the current study. The findings indicate that ARIMA (2,0,2) and (2,1,2) conducted an adequate performance in predicting upcoming outbreaks. According to the anticipated findings of this study in the District of Toba Tek Singh, the monthly incidence of Dengue cases peaked in May and increased steadily from March through September. This time-dynamic pattern indicated that the forecast had a substantial seasonal effect. It is remarkable that the outbreaks in Indonesia in 2014, which had the highest incidence in May, were similar to the maximum anticipated incidence in May (Othman *et al.,* 2022). As a result, this forecast based on the ARIMA (2,0,2) and ARIMA (2,1,2) model offers future Dengue spread numbers and may be used to help government officials and public health professionals design efficient public health measures to avoid and manage the disease, especially in the initial phases of outbreaks.

According to District Jhang's 2024 projection, there will be a seasonal peak in August with 750 expected cases. The ARIMA model was created using data obtained between March 2019 and December 2022. The model's validity was evaluated by estimating monthly DHF cases for this region for 2023 and 2024. The projected values appeared to properly reflect the ups and downs of the observed series. The cases demonstrated a seasonal pattern, peaking in September, similar to previous climate variations. A new study in Jeddah, Saudi Arabia, used time-series data from 2006 to 2016 to anticipate DHF mortality as well as morbidity for the years 2017 to 2019 (Abualamah *et al.,* 2021).

In Pakistan, DHF is a significant public health concern. This is mostly caused by an annual increase in exceptional incidents. As a result, only a few outbreak prevention strategies have been put into practice. To help the public and authorities respond to outbreaks effectively and make sufficient preparations for raising public awareness, the current research attempted to predict the incidence of Dengue using an efficient forecasting method. The data demonstrated that there was a distinct seasonal pattern to the disease, with the highest occurrences between May and September. Similar to this, Rajasthani researchers created a forecasting model for DHF utilizing time-series data from the last ten years to predict monthly Dengue Fever/Dengue hemorrhagic incidence for 2011. Climate changes have been linked to the occurrence of DHF (Morales *et al.,* 2016).

CONCLUSION

In conclusion, the fastest-rising vector-borne illness in tropical, subtropical, and underdeveloped countries is Dengue. For this study, monthly data from 2019 to 2022 on diagnosed DHF cases in the Toba Tek Singh and Jhang districts of Punjab were collected to predict disease outbreak in its early stages and facilitate prompt action. Monthly DHF occurrence patterns were examined to create efficient forecasting models. Then, the most accurate models were used to predict the frequency of Dengue Fever cases between 2023 and 2024. The incidence of DHF data showed a strong seasonal influence. These results demonstrated a rise in DHF patients between March and September. Additionally, every three years—between 2019 and 2024—the Dengue outbreaks seemed to peak higher in September. It is believed that the primary factor responsible for DHF cases is the air temperature.

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